Report on the Code
PD-Internship
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06/05/2018

Some of this report was originally present in report #4. However, since it's prone to update unlike the rest of report #4, on April 19th I split the report in 2 : Literature review and Code. This is the Code one.
In parallel I read about online HaW analysis and thus wrote report #5.

Disambiguation : All the results were obtained on the *spiral* task if not specified otherwise.

Until April 25th, all experiment results were obtained while validating on the test set (see 5 Evaluation and experiments for discussion). Therefore, I added "**[Validation accuracy !]**" after all these results. Moreover, you'll see on the most of the plots that there's only two curves : "train" and "validation", this is because there was no proper test set.

Cf. Git Commits and the experiment results.

Overview

1 Model architecture

We use the LSTM as defined in PyTorch[1], thus, for each element in the input sequence, each LSTM unit of each layer computes the following operations :

$$
\begin{aligned}
i_t &= \sigma(W_{ii}x_t + b_{ii} + W_{hi}h_{(t-1)} + b_{hi}) \\
f_t &= \sigma(W_{if}x_t + b_{if} + W_{hf}h_{(t-1)} + b_{hf}) \\
g_t &= \tanh(W_{ig}x_t + b_{ig} + W_{hg}h_{(t-1)} + b_{hg}) \\
o_t &= \sigma(W_{io}x_t + b_{io} + W_{ho}h_{(t-1)} + b_{ho}) \\
c_t &= f_t c_{(t-1)} + i_t g_t \\
h_t &= o_t \tanh(c_t)
\end{aligned}
$$

Where h_t is the hidden state at time t, c_t is the cell state at time t, x_t is the input at time t, $h_{(t-1)}$ is the hidden state of the layer at time t-1, and i_t, f_t, g_t, o_t are the input, forget, cell, and output gates, respectively. σ is the sigmoid function. W_* are the weight matrices and b_* are the bias vectors.

Baseline decoder : We currently feed the last hidden state of the LSTM (summed if bLSTM) to a FC layer with a single neuron which is used for binary classification after applying a Sigmoid to it. The Sigmoid function is an activation function which is defined as :

$$f(\hat{y})_i = \frac{1}{1+e^{\hat{y}_i}}$$

The input is a time-varying sequence (2k timesteps in average) where each timestep is a vector containing 7 measures : y-coordinate, x-coordinate, timestamp, button_status, tilt, elevation, pressure.

[1] https://pytorch.org/docs/stable/nn.html#torch.nn.LSTM

We train the model using Adam optimizer (Kingma & Ba) which is based on SGD. The optimizer minimizes the Binary Cross Entropy Loss, which is defined as :

$$L = y^{(i)}\log(f(\widehat{y^{(i)}})) - (1-y^{(i)})\log(1-f(\hat{y}^{(i)}))$$

Where y is the ground truth, aka the target aka the label (i.e. 0 for control and 1 for PD) ; $\hat{y}$ is the prediction of the model and $f(*)$ is the Sigmoid function, defined above.

Our dataset is challenging :

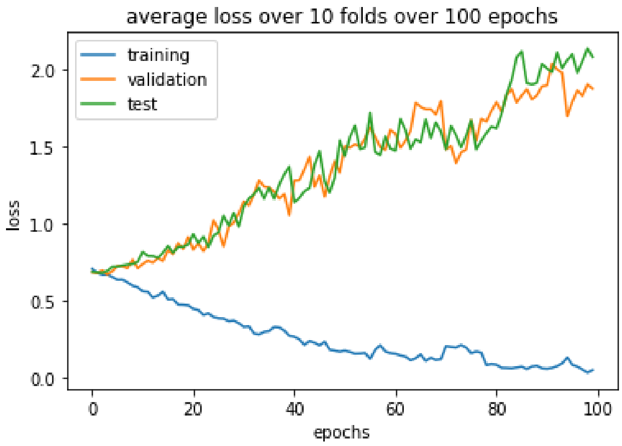
1. by its very small number of sample
2. by its very long and varying sequences

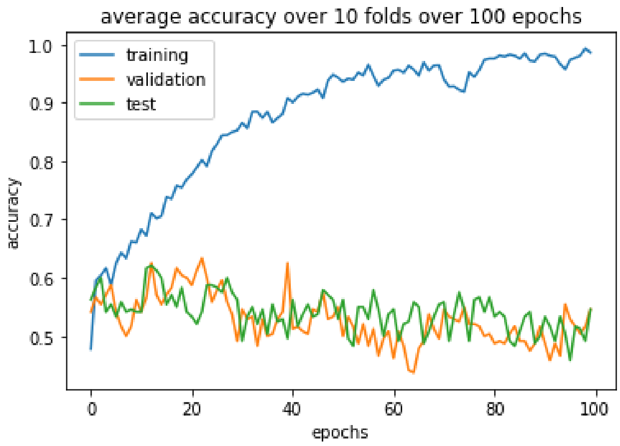
Thus our model should be complex enough to capture the long sequences but not too much or heavily regularized so it won't overfit the very little number of samples.

With a very simple model (**baseline**) :

- *learning_rate* $= 10^{-3}$
- *hidden_size=100*
- *num_layers=1*
- *bidirectional=False*
- *dropout=0.0*
- *no gradient clipping*
- → **43 701** total parameters, all *trainable*.

We're able to fit the training set (80% of the dataset), cf. figures below.





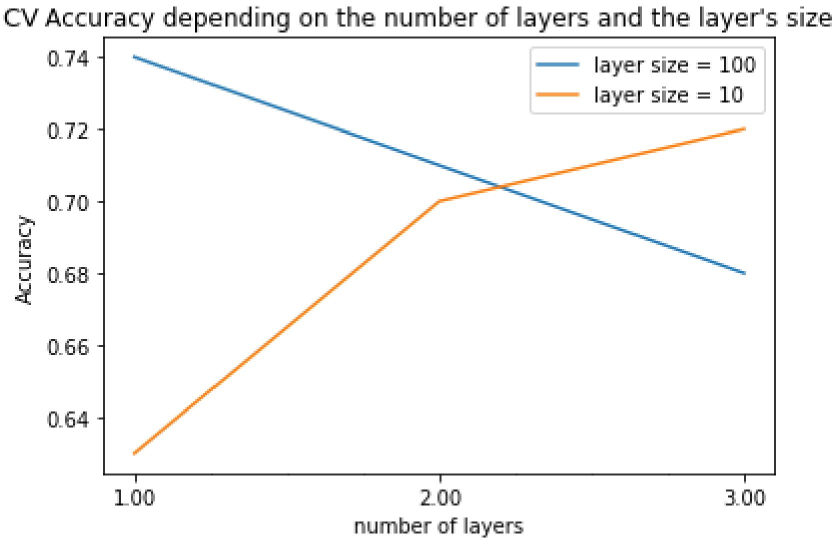
Although the model starts overfitting after 1, 2, 1, 4, 4, 2, 4, 3, 5 and 1 epochs (out of 10 folds, respectively).

We don't use mini-batch as the sequences in our dataset are of very different lengths and we have not found a way of packing them efficiently.

Using a bidirectional LSTM consistently improved the results over the *spiral* task.

There is a lot of interaction between the layer size and the number of layers, we can observe a reversed effect, see figure below. The other hyperparameters are fixed to :

dowsampling factor	**learning_rate**	**bidirectional**	**carry over**	**dropout**	**gradient clipping**
1	0.001	TRUE	0	0.5	5



[Validation accuracy !]

This can probably be explained by the n° of parameters :

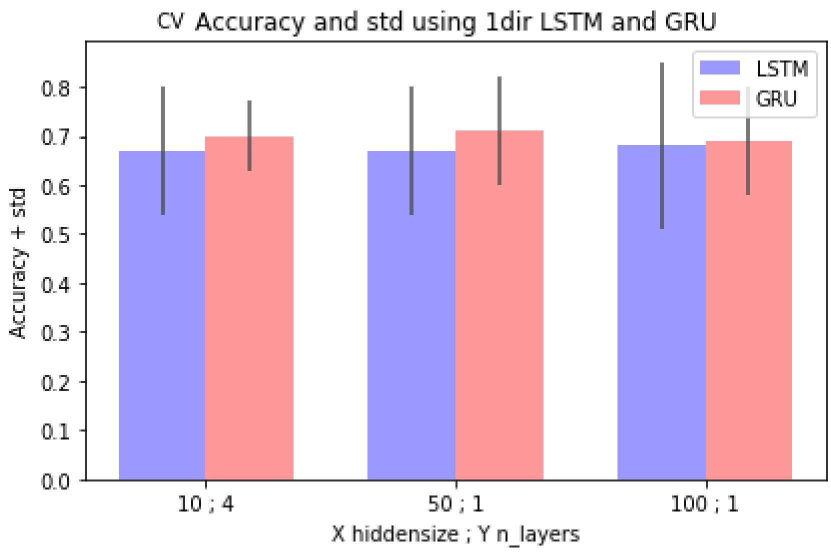
layer's size	n° layers	n° of parameters
10	1	1531
10	2	4091
10	**3**	**6651**
100	**1**	**87301**
100	2	328901
100	3	570501

Therefore, the optimal n° of parameters of the network is probably between 6k and 90k, when using the current regularization techniques (i.e. 50% feedforward dropout). To confirm this hypothesis, I tried with *hidden_size=50 num_layers=1* → **23651** parameters and achieved similar results. However with *hidden_size=50 num_layers=2* → **84451** parameters the results were slightly inferior. Thus we should privilegiate the number of layers over the hidden size for the same numbers of parameters. Although this could be explained because of our regularization techniques (i.e. 50% feedforward dropout), if we'd apply recurrent dropout the results might be different. **[Validation accuracy !]**

Among this similar results, I prefer to stick with the simpler (i.e. with less parameters) model which is less prone to overfitting :

Fig. Left : ***hidden_size=10 num_layers=3*****, right :** ***hidden_size=100 num_layers=1*****. Different scales**

Using a 1d GRU consistently improved results and decreased std over 1d LSTM **[Validation accuracy !]** :



I performed a random search on the l task on :

- *learning_rate* in {0.01, 0.001, 0.0001}
- *num_layers* in {1, 2, 3, 4, 5}
- *hidden_size* in [[1, 200]]
- *bidirectional* in {True, False}
- *dropout* in [0, 1]

With an extra constraint : $num\_layers * hidden\_size < 300$ in order to limit the n° of parameters. The random search performed 59 experiments (10-CV) in 3 days. Unfortunately it didn't get better than my manual fine-tuning. We should be very careful of the cross validation results because of the early stopping. One set of parameters achieved 70% validation accuracy but had only 51% training accuracy so I had a look and the model was almost random (cf figure below). Almost all experiments results have better training than validation accuracy. Although this is partly explained by the early stopping (cf. 5 Evaluation and experiments), it is also because we first train the model before validating so a more relevant comparison would be between validation accuracy at epoch e and training accuracy at epoch $e + 1$. Also, dropout is only active while training so the training accuracy should be higher than the validation one if there's dropout.

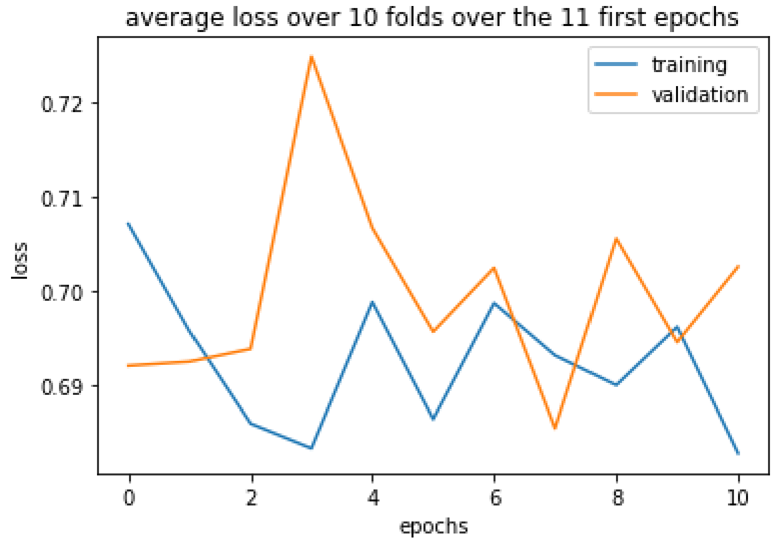


Fig. Model that doesn't fit but get's 70% accuracy on the l task

Following advices of Jozefowicz et al. 2015 (cf. report #4), we initialize the bias of the forget gate to 1 when using an LSTM as encoder.
It improved training accuracy, validation PPV and reduced the variance (std) on the small baseline model with 2 layers (colored in red in the experiments results).

2 Model training

Fig. Baseline model ([1 Model architecture](#)) : on some folds the model won't fit the data very well (left : typical fold, middle : hard fold, right : clipped hard fold) /!\ Different scales /!

It may be because of exploding gradients : clipping the gradients norm to 5 helped with this (cf. figure).
Although it didn't help with the cross validation results, on the contrary, they are slightly inferior compared to the ones without gradient clipping. The differences between these results might also be explained by the random initialization of the weights of the network. I set the random seed after the first few experiments to avoid this bias.

Unlike with *spiral* above, clipping the gradients to 5 didn't have any effect on the *l* task (with lr= 10^{-3} or 10^{-4}).

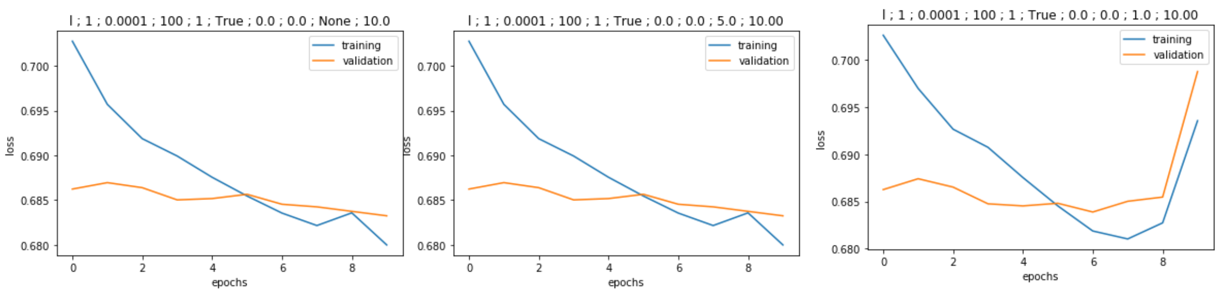


Fig. Left : no gradient clipping, middle : gradient clipping at 5, right : gradient clipping at 1.

Note : on these above experiments and untiil May 2nd, I used to clip both encoder's (i.e. LSTM or GRU) and decoder's (i.e. FC layer) gradients. Whereas gradient clipping should only be applied to RNNs which have the exploding gradients problem. Therefore, on may 2nd I tried to clip only the encoder's gradients and it didn't have any effect on the model :

task	model	learning_rate	hidden_size	num_layers	bidirectional	dropout	gradient clipping

I	**paper_air LSTMs, 1 decoder**	0.001	10	4	FALSE	0	5

According to these first experiments, the best learning rate is 10^{-3}. With 10^{-4} there is more variance (std) and on some folds the model is overfitting from the first epoch (cf. figure below), we might try it again along with regularization techniques.

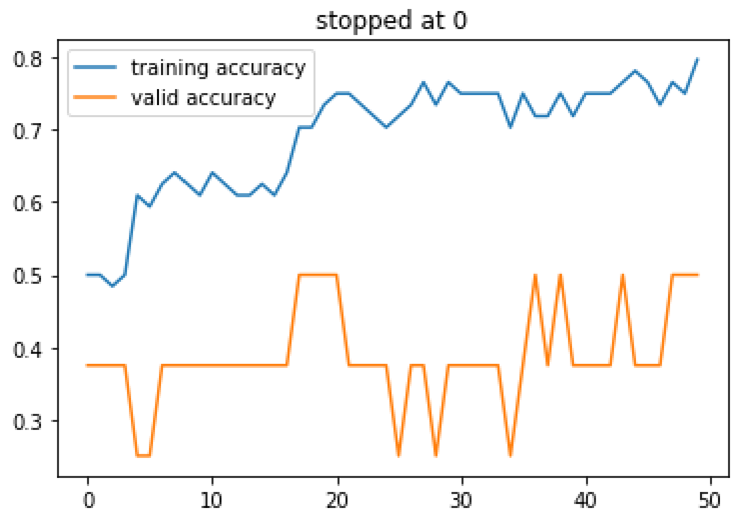


Fig. LR = 10^{-4}, model is overfitting from the first epoch

I tried to train the model "continuously" by "passing on" the hidden state from one subject to another (i.e. the hidden state is not init to 0 but to the previous hidden state).
This makes the loss more unstable as you can see below. I highlighted the results in purple in the results summary. Although one can notice that the training loss is similar between the 2 conditions. It's quite strange given that there's no dropout so maybe the changes in the validation loss are not significative.

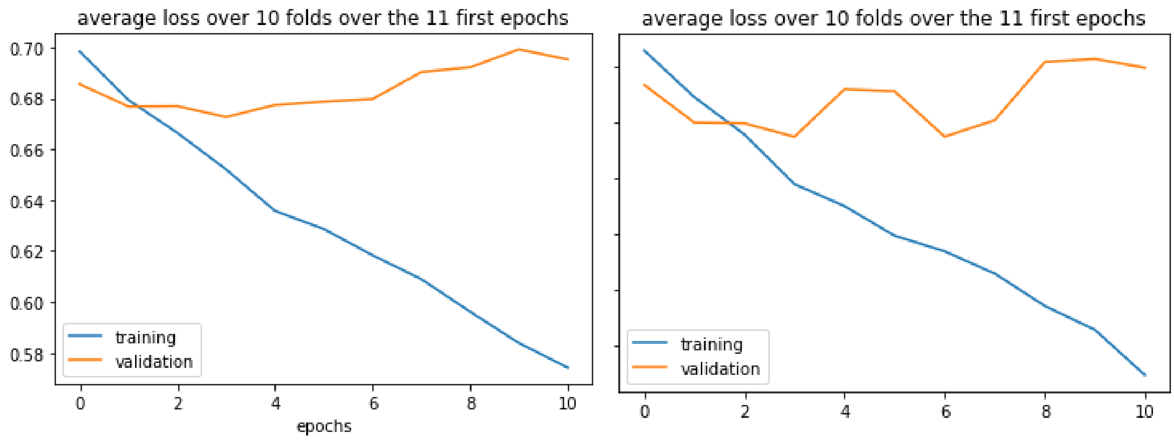
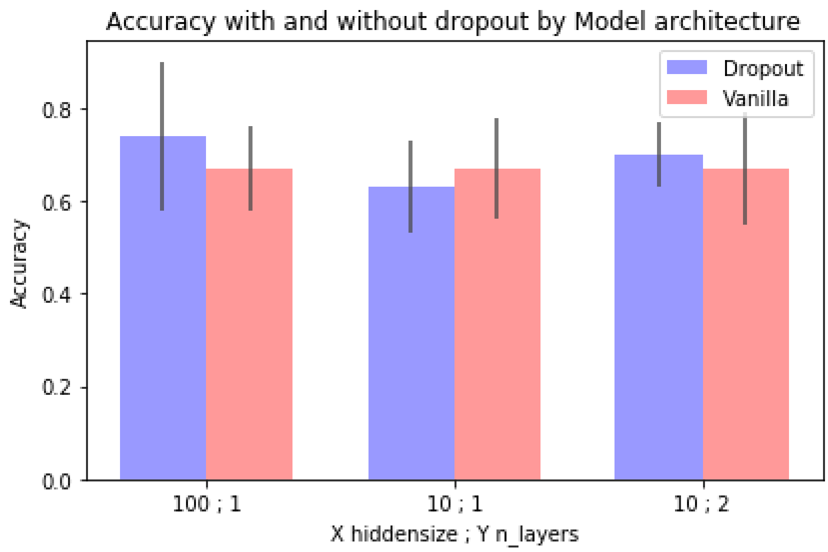


Fig. Continuous learning. Left : no, right : yes.

3 Regularization

Consistently with Lipton et al., adding a dropout of 0.5 between the non-recurrent layers enhances the results with large layers and stacked LSTMs. See figure below, all the other hyperparameters are fixed to :

dowsampling factor	learning_rate	bidirectional	carry over	gradient clipping
1	0.001	TRUE	0	5



[Validation accuracy !]

Interestingly, this is specific to LSTM, using feedforward dropout on GRU had very little effect...

Fig. From left to right : 1GRU with and without dropout, bGRU without dropout (different scales)

4 Data

4.1 Exploration

After discarding subjects who didn't perform the *spiral* and task and counting from 0 :
The tasks 0, 1, 4, and 7 from subjects 56, 9, 39 and 67, respectively, started their exam while pen was in air (i.e. not on paper). All these subjects are control except for n° 9.
As you can see below it's neglectable for subjects 56 and 67 but leads to quite different plots for subjects 9 and 39.

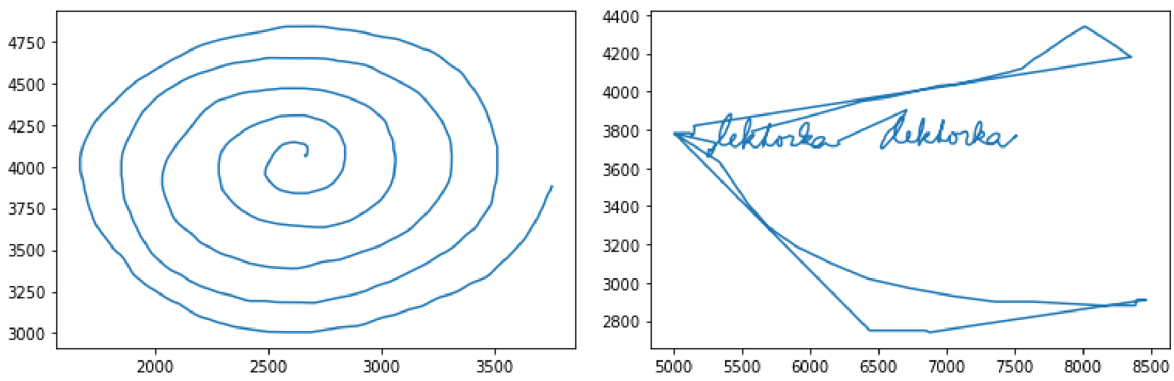


Fig. Exam starting in air. Left : *spiral* of subject n° 56, right : *lektorka* of subject 39. Both are controls.

After investigation I found that most of the exams contained (really) small pauses.

Therefore, the timestamp measure might be useful so the model has a sense of these pauses.

4.2 Preprocessing

Standardizing a vector (e.g. x-coordinate of a task) gives it a mean of 0 and a standard deviation of 1. Normalizing a vector gives it a norm of 1.

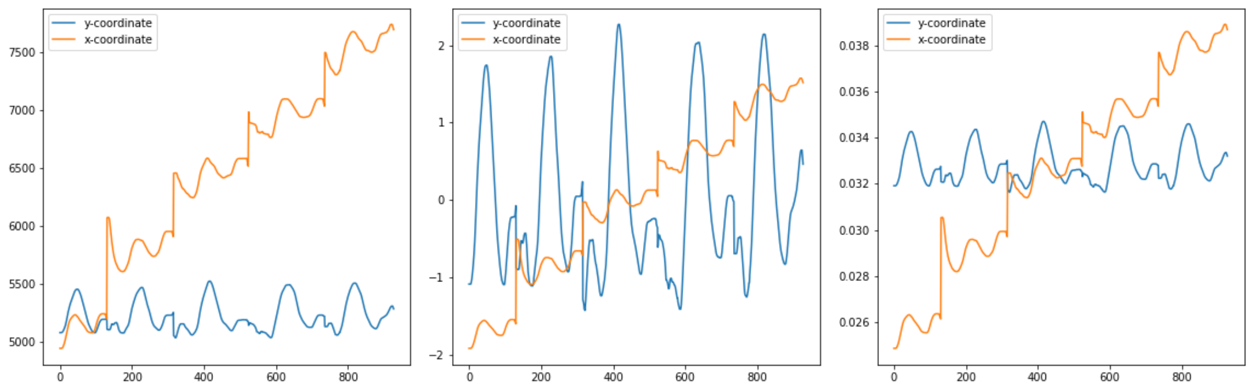


Figure of the x and y coordinate (for readability reasons) recorded at 200Hz for the second task (writing multiple "l") of the first subject (PD) : raw, standardized and normalized (from left to right).

One can notice that the data ranges are preserved when normalizing unlike when standardizing. So I'd assume that it was better to normalize than to standardize but after experiment, the model won't fit the data if it's normalized, although it fits it quite well if it's standardized. After investigation I noticed that, between subjects, the normalization shifted the values of the data : you can see here that for the first subject the normalized x coordinate ranges between 0.026 and 0.038, whereas for the 26th subject, it ranges from 0.022 to 0.028 (although the raw ranges are similar). If we feed the raw data to the model (i.e. without any type of normalisation) it doesn't fit to the data : with $lr = 10^{-2}$, the loss converges at 0.7 (accuracy 0.469). Tried with $lr = 10^{-3}$ (converges higher), $lr = 10^{+1}$ (doesn't converge).

Downsampling the data 10 times doesn't help with the overfitting as you can see in the experiment results (column downsampling factor).

4.3 Representation

The model is *not* able to fit the data when training on all tasks at once. Although we're concatenating a one hot vector to the measures which identifies the task (e.g. [0., 1., 0., 0., 0., 0., 0., 0.] for the l task). This might be considered an early fusion technique which augments the dataset. We might want to compare it to late fusion techniques (e.g. majority voting).

In order to be able to implement *attention* (cf. Report #4 1.1 Model Architectures et al.) I tried trimming and padding with zeros the spirals that were respectively longer and shorter than 3117 timesteps (3rd quartile of the spirals' length) and the model won't fit the data with the same hyperparameters as without trimming and padding.

Inspired by the work of Zhang et al. (cf. report #5). I tried to split the model into subsequence with a fixed time window of 100 timesteps. Unfortunately, the model is completely unable to generalize and the validation accuracy never gets better than chance level, although the model fits the training set. Dropout was ineffective. I should maybe try other segmentations, e.g. stroke, also I might want to train 2 separate models on in-air and on-paper strokes, respectively. This is motivated by the experiment results which are superior on the $spiral$ task where the single stroke is on-paper. As opposed to the l task where strokes are both on paper and in-air. Since in-air movements are very different from on-paper ones, I think they might disturb the model.
Interestingly, computing the movement (cf. report #5) had no effect when the data was split in subsequences but improved the results when training on the whole sequence, although Leo told me it shouldn't be necessary when using a RNN, therefore, further experiments are required.

I tried to split the l task into strokes then to train 2 different encoders :

- one on the in_air strokes and
- one on the on_paper ones.

I tried to use 2 separate decoders as well as 1 shared. The predictions are then averaged over each subject to get a final prediction (as in the fixed-time window experiment). The results are not encouraging and similar to "whole sequence"-training on the l task : we get around 70% accuracy on the validation with very high std on (between 15% and 20%) and we barely go above chance level on the test set.
When using a single model over the strokes (thus learning both in_air and on_paper strokes simultaneously) the test accuracy falls behind chance level. Even though we feed the button_status unscaled thus indicating whether the stroke is in_air or on_paper.

4.4 Augmentation

I tried 5 different heuristics of data augmentation : 4 applicable only to spatial coordinates : flips, rotations, translation and homothetic (i.e. "zoom"), 1 applicable to all measures : gaussian noise. I made the assumption that gaussian noise would be ineffective since PD suffer from tremor which translates into a "noisy" signal. Moreover, Graves 2012 (cf. Report

#4) argue that Gaussian input noise is only effective if it mimics the true variations found in the data, e.g. for speech recordings.
All augmentations were applied both to the training and the validation set because one of the main goals was to augment the validation set in order to have a better representation of the model generalization capacity to perform early stopping (cf. 5 Evaluation and experiments).
In order to have a dataset size of the same order between these 5 heuristics, I applied 3 transformations every time (cf. figures below), thus multiplying the number of training examples by 4.

None of these augmentation heuristics provided encouraging results, although I only tried with one set of hyperparameters.

4.4.1 Flips

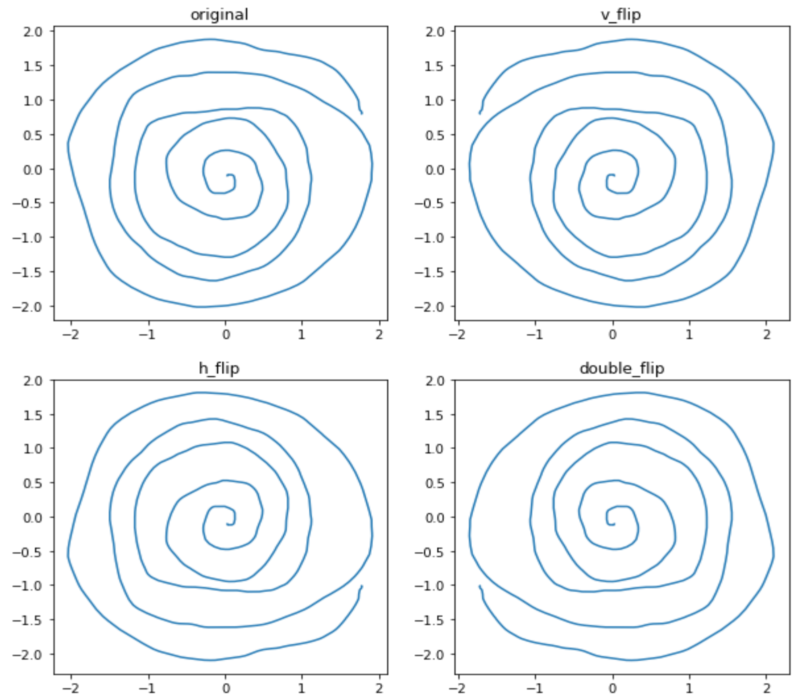


Fig. Flips : original data, vertical flip, horizontal flip, and both horizontal and vertical flip

For the flips I empirically choose a symmetry axis along which to flip the data, e.g. for the vertical flip, I transposed every point with respect to the vertical axis (i.e. the first x point).

4.4.2 Rotations

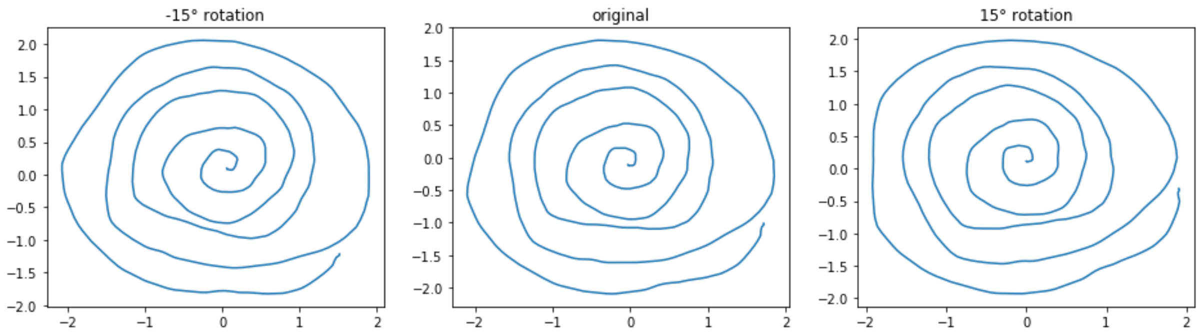


Fig. Rotations. Data is re-centered after rotation.
To have a dataset size of the same order as with flips I performed a third rotation of +30°.

4.4.3 Translations

Before each training step I choose a random number between -0.5 and 0.5 (as the standard deviation of the data is one). I then apply 3 different types of translations :

1. translation along the x-axis
2. translation along the y-axis
3. translation along both x-axis and y-axis

4.4.4 Homothetic (i.e. "zoom")

An homothety is a linear transformation where we multiply a vector by a scalar. Therefore when the vector is a spatial coordinates we "zoom" or "de-zoom" the image when the scalar is greater and smaller than 1, respectively. In order to have data ranges comparable to the translation, I choose a random zooming factor between 0.8 and 1.2, as the standardized spirals coordinates ranges from ~-2 to ~2 and the translation ranges in [-0.5, 0.5]. As for the translation, I performed 3 types of homothety :

1. homothety along the x-axis
2. homothety along the y-axis
3. homothety along both x-axis and y-axis

4.4.5 Gaussian noise

I choose to add gaussian noise on all the measures with standard deviation of 10^{-2} as it's almost invisible for the naked eye on the pressure. With std = 10^{-3}, the variations of the spatial coordinates are also invisible for the naked eye. I called this experiment "naïve noise" because I add gaussian noise on all measures, even timestamp and button_status.

I conducted another experiment with noise only on noisy measures. Namely, tilt, elevation and pressure (which are noisy independently of PD and controls). I called it "noise on noisy". It provided better results than naïve noise but didn't improve the baseline (without augmentation).
In order to have a data size of the same order as the previous heuristics, for each data sample, I made 3 random noisy variants when training and validating, thus multiplying the data size by 4.

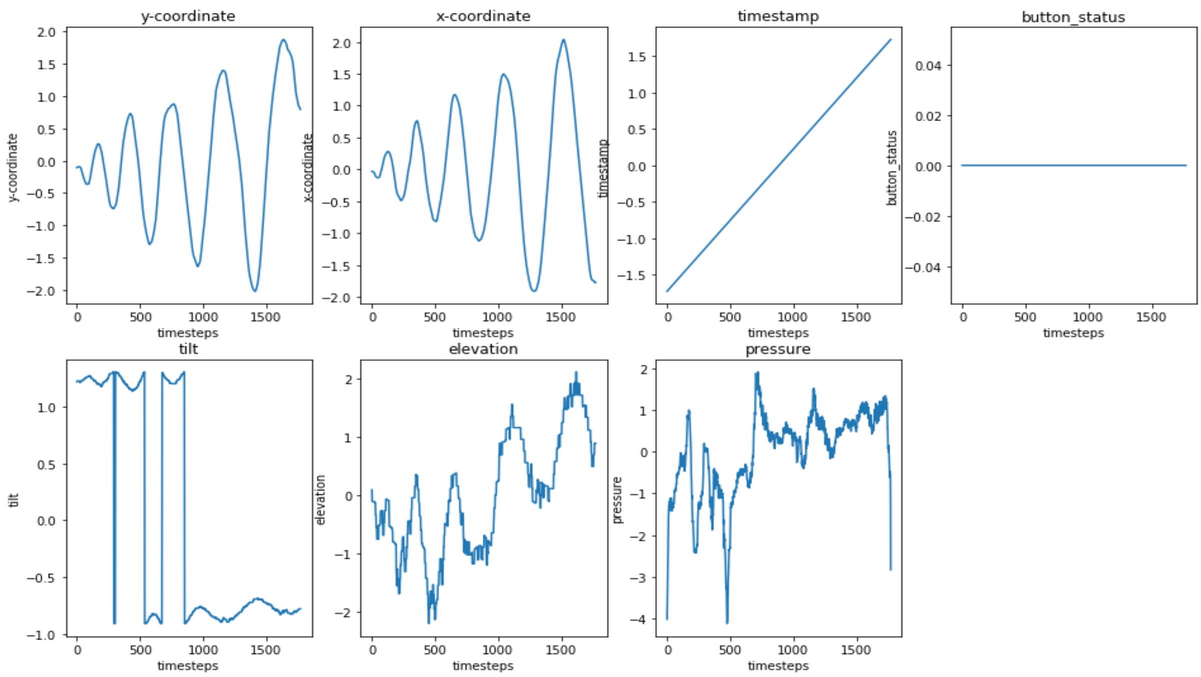


Fig. All 7 measures plotted against time for the first subject spiral. We can see that tilt, elevation and pressure are noisy unlike spatial coordinates, timestamp and button_status.

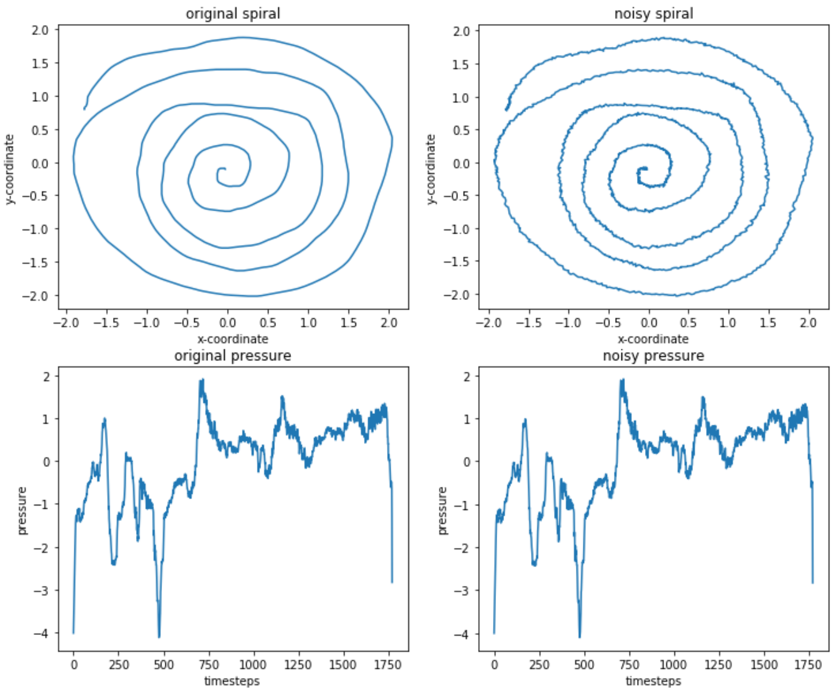
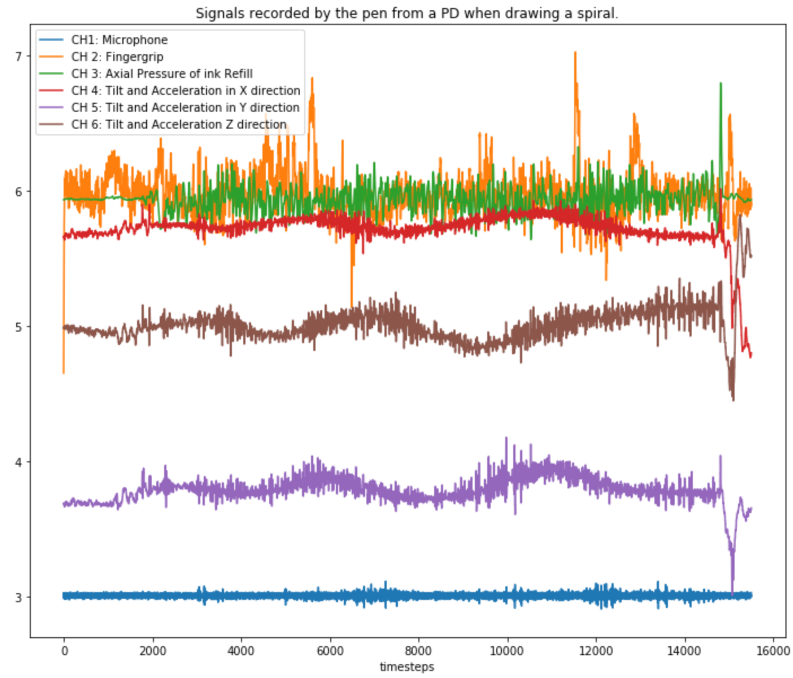


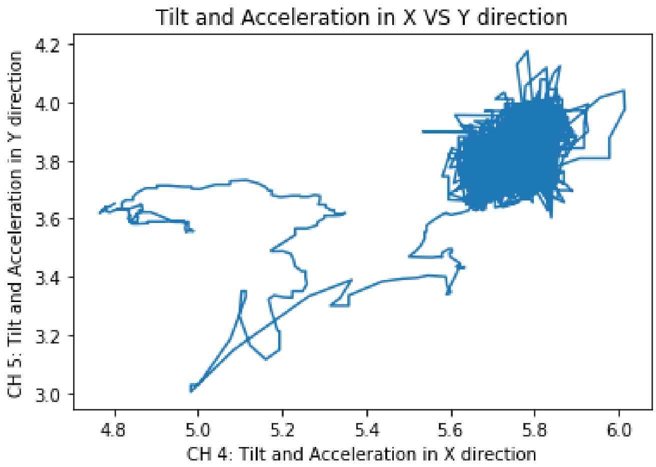
Fig. First subject spiral, with and without gaussian noise with 10^{-2} std.

4.5 NewHandPD

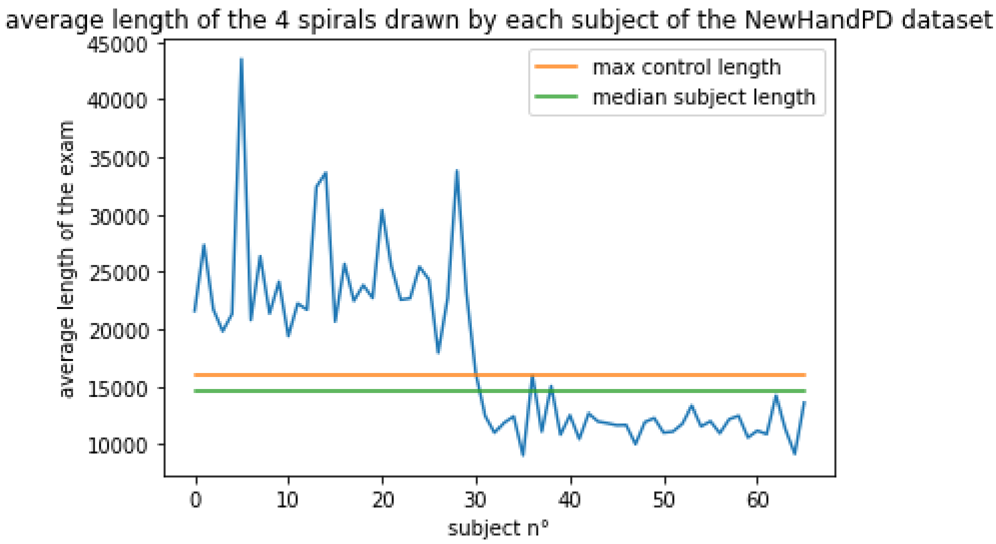
Hoping to achieve transfer learning I took a look at the NewHandPD database of Pereira et al. (cf. Report #2). However I'm not sure we'll be able to achieve transfer learning between NewHandPD and PaHaW as NewHandPD doesn't record the x and y coordinate but the "tilt and acceleration" in both x and y directions.



Thus the plot of X vs Y is not visually interpretable.



This dataset is a joke ! I achieved 100 % accuracy, Se, Sp, PPV, NPV with a simple rule based on the average exam length of the 4 spirals drawn by each subject. Cf. figure below where the first 30 points represent PD and points 31 to 65 represents controls, we can clearly see a threshold, displayed here as the maximum average length of the controls' exam.



When setting the threshold at the median length for all subject (thus not needing any knowledge/learning about PDs and controls), I achieve :

Accuracy	Se	Sp	PPV	NPV
0.97	1.00	0.94	1.00	1.00

This is the best accuracy on this dataset (cf. Report #2). It's completely crazy, I find it hard to believe. Maybe you should check the *newhandpd* notebook to see if I didn't do any mistakes but I can't think of anything which would bias those results.

To further confirm those results, I trained a neural network with a single neuron, Sigmoid activation and binary cross entropy loss using the Adam optimizer with a learning rate of 10^{-1}. After one epoch, I achieve (average over the 10 folds + std) :

Accuracy	**Se**	**Sp**	**PPV**	**NPV**
0.98 + 0.05	0.97 + 0.1	1.0 + 0.0	1.0 + 0.0	0.975 + 0.075

Moreover, I used sklearn implementation of Linear Discriminant Analysis and obtained similar results.

From that I think we can conclude that the transformation of the data from sensor to image of Pereira et al. is not good or that CNN are not suited to discriminate PD and one should focus on kinematic features. Also, it does not encourage the use of Discrete Wavelet Transform as did Afonso et al. (cf. Report #2).

5 Evaluation and experiments

8	8	8	8	8	8	8	8	6	6

Fig. 10 fold Cross-validation (CV) configuration until April 25th. The numbers represent the number of subjects in each fold. Training set is colored in blue while the validation/test set is colored in green.

Average metric over the 10 folds (+ standard deviation) after early stopping (i.e. we select the best epoch based on the validation accuracy for each fold). For the baseline model depicted in 1 Model architecture.

TRAIN accuracy	**accuracy**	**Se**	**Sp**	**PPV**	**NPV**
0.59 (+ 0.07)	0.68 (+ 0.09)	0.54 (+ 0.20)	0.82 (+ 0.20)	0.81 (+ 0.20)	0.65 (+ 0.08)

[Validation accuracy !]
Every metric is for the validation set if not specified otherwise (i.e. except for the first column). Since the validation set is very small (~ 7 subjects) the metric standard deviation

(std) is very high, this is consistent with Moetesum et al. (cf. Report #2). The accuracy for the *spiral* task is 76%, 63% and 55% for Moetesum et al., Drotar et al. and Impedovo et al., respectively. Notice that, in the same way as Drotar et al., we validate on the test set (i.e. on the validation fold). Therefore our results are over optimistic and possibly overfitted to the dataset.

I tried to train the model without early stopping for 4 epochs (because the model usually overfits after 4 epochs) with the GRU depicted in 1 Model architecture. The accuracy is slightly decreased and the std augments : from 70% to 65% and from 8% to 13% respectively. Moreover, these results are also "overfitted" to the test set because if we train for one more epoch they get worse so I didn't present them.

I also tried to implement a proper early stopping by splitting the dataset in training, validation and test set and early stopping according to the validation results. However in this case the results are even worse, only 61% accuracy and 17% std.

I don't think the problem is that the training set is too small because if we take the best epoch for each test folds we get the same results as before : 71% (+ 11%) accuracy. The problem is that since the validation test is very small, it's not very representative of the generalization capacities of the model. On average the validation loss and the test loss are quite similar (cf. figure below) but on some folds they're very different. We might try to do data augmentation on the validation set so it's bigger and thus more representative of the capacities of the model.

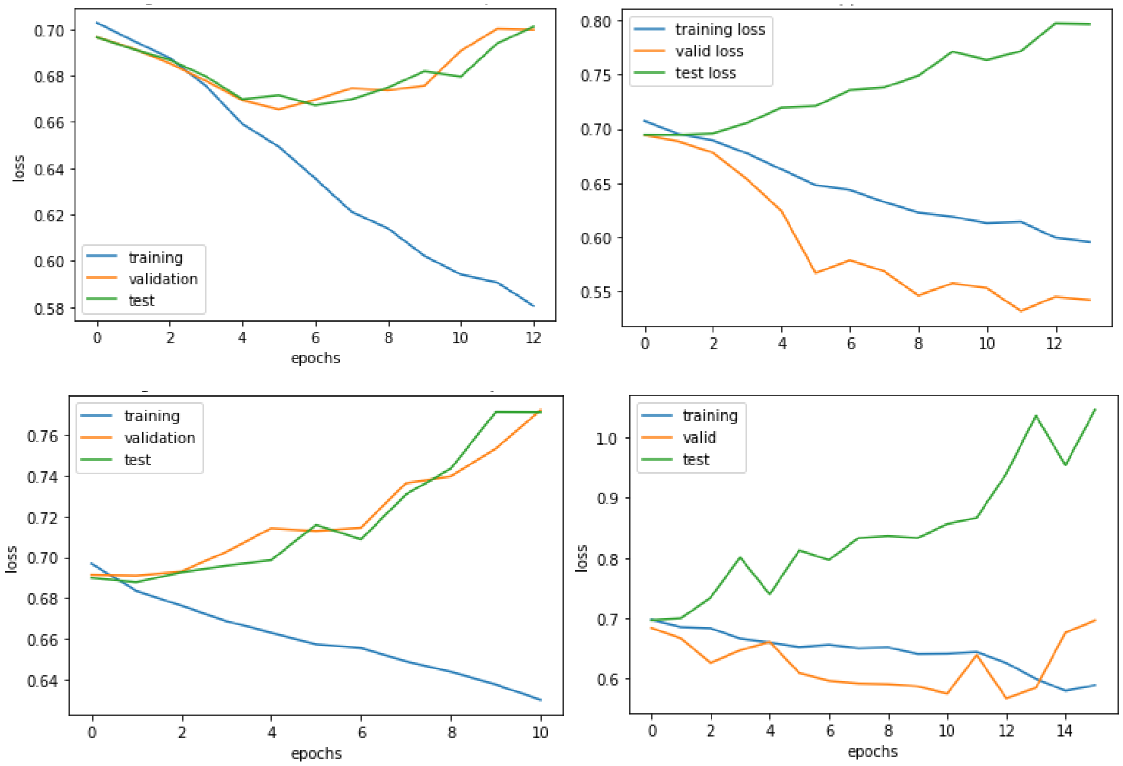


Fig. Left : average loss over the 10 folds, right : loss on the first fold. First row : no data augmentation. 2nd row : Flips (similar with rotations, homothety, naïve noise and translations).

8	8	8	8	8	8	8	8	6	6

Fig. 10 fold Cross-validation (CV) configuration after April 25th. The numbers represent the number of subjects in each fold. Training, validation and test sets are colored in blue, orange and green, respectively.

Even though these results are disappointing, I think we should stick with one of these methods because Drotar et al. validate on the test set for hyperparameters search (as us), not for the n° of epochs etc. I hope we will be able to conjecture from the previous experiments results which were over optimistic. As the data augmentation did not improve the results (cf. 4.4 Augmentation), I think we should not perform early stopping and train for fixed n° of epochs.

Following the guidelines of Greff et al. (cf. Report #4 1.2 Hyperparameters finetuning), we should be able to fine tune the hyperparameters independently, starting from :

- learning rate

- hidden size
- number of layers
- regularization techniques (e.g. dropout, although Karpathy[2] and Lipton et al. suggests that it interacts with the hidden size so we might want to tune these hyperparameters together)

Throughout these experiments we shall use a bidirectional LSTM, which can only better the results in my opinion (cf. 1 Model architecture). Also the decoder architecture will be kept as simple as possible (cf. 1 Model architecture). I made this choice because I assume that the "hard part of the job" is made by the LSTM and not the decoder.
I thought we might also use an SVM as Moetesum et al. or OPF as Passos et al. 2018 (cf. Report #2) but we can't because unlike them we need to train the network (they use a CNN pretrained on ImageNet).
All the results of the experiments are available in the git repo. The studied hyperparameter is print in **bold**.
Note :

- the max epochs was set at 5 for the lines 20 and 21, 10 for the lines 22 and 23 and 50 for the rest
- there was no patience for early stopping for the lines 20 to to 26 but no improvement was okay : you can see the differences between line 26 (which is greyed out) and 27. They are probably explained because when we tolerated the lack of improvement, the model could wait for tens of epochs (cf. "early stopped"), overfitting until "by chance" the accuracy would went up (cf. figure below : left for accuracy, right for loss). Thus the **results of lines 26 are overoptimistic**.
- the seed for random weights initialization was not fixed for the lines 20 to 26. Therefore a direct comparison with and between those might be biased.
- Some "falses" are greyed out, it's because they represent subject indexes before discarding the 3 subjects who didn't perform the spiral task. Therefore these index don't match the other ones.

[2] https://github.com/karpathy/char-rnn

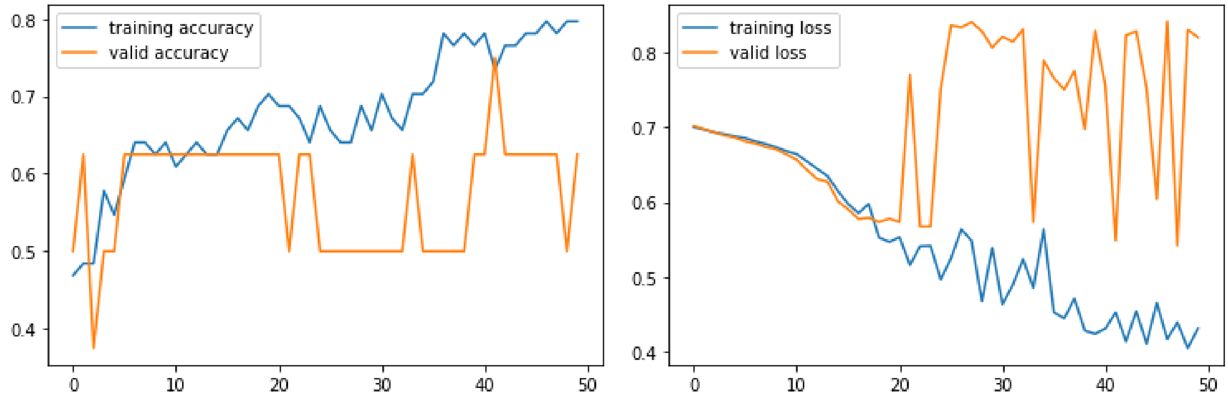


Fig. Model overfitting until (probably) random amelioration (line 8). Left : accuracy, right : loss.

6 Visualization & Interpretation

6.1 Input weights

Karpathy, Johnson et al. wrote a great article about visualizing RNN, however, their classification task (language modeling) allows for a simpler interpretation. I tried visualizing the input weights of a model fitted to the data in order to see which of the 7 measures was activated. As you can see below, the weights differ along the layer (i.e. between the GRU units) without any measure standing out (I also tried plotting each measure along the layer or compute the mean of each measure). One possible interpretation is that there's no measure which is consistently "interesting".

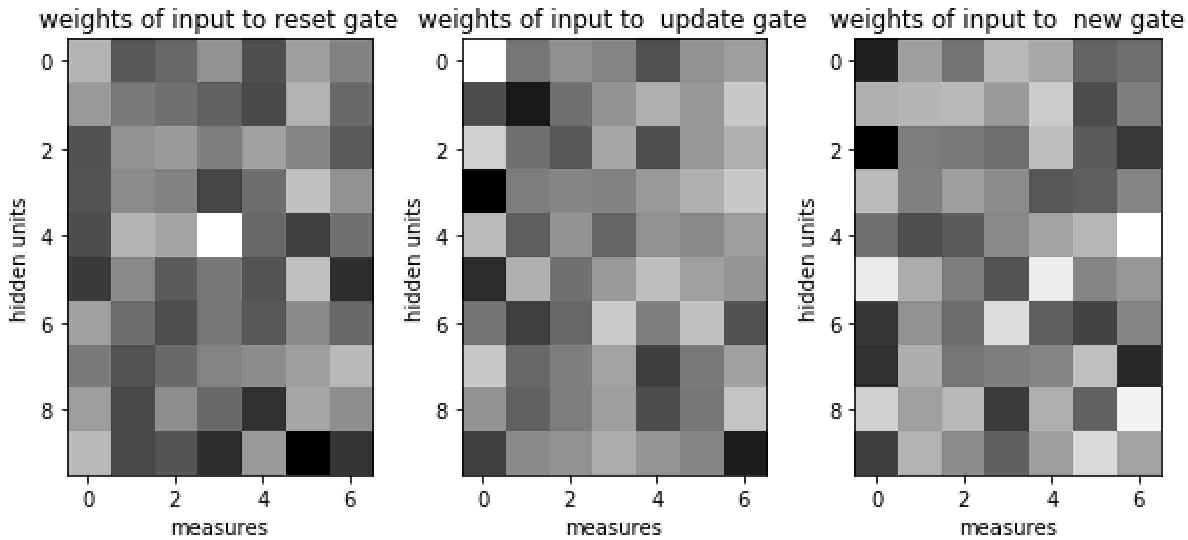
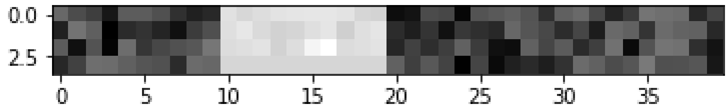


Fig. Plot of the weights of the hidden units (of the first layer of the network).

6.2 Forget Gate

Interestingly, after using the trick of init the forget gate bias at 1, even after 22 epochs and an overfitted model, the bias of the forget gate are still worth ~1 (cf. figure below). One possible interpretation is that the model learned to *remember* the previous value of the *cell state*.



6.3 Misclassified subjects

For the model with hyperparameters :

dowsampling factor	**learning_rate**	**hidden_size**	**num_layers**	**bidirectional**	**carry over**	**dropout**	**gradient clipping**
1	0.001	**50**	1	TRUE	0	0.5	5

I looked into which subjects had been misclassified when the model had early stopped (i.e. when the classification accuracy was highest). It turns out that, among the misclassified subjects (22 over all 10 folds), 3 of them had performed very long exams of 16071, 9724, and 8581 timesteps. Thus bringing the average length of misclassified subjects to 3552 instead of 2758 (average over every subjects). It'd be interesting to see if the same subjects are misclassified across models.

Conclusion - Todo List

I followed my intuition and explored the hyperparameters fine-tuning of our current model on the *spiral* task. I found that GRUs were less prone to overfitting than LSTMs, although feedforward dropout was efficient for regularizing LSTM. Thus, stacked LSTMs give better results than long, single layers. In the experiment results, I colored in green the hyperparameters that worked well together, as well as all the learning rates and gradient clipping which I found the best values to be 10^{-3} and 5, respectively. Again, all the experiments with "proper_early_stopping = False" were conducted while validating on the test set (cf. 5 Evaluation and experiments) so I hope the results are still valid when running a proper CV.

Then I tried, without success, to learn from all tasks at the same time, then to learn from fixed-time subsequences (cf. 4.3 Representation).
Data augmentation didn't provide encouraging results (cf. 4.4 Augmentation) so I think we should not perform early stopping and we might consider using a larger dataset or change model.

Also, I think my work on 4.5 NewHandPD is interesting and might deserve a paper.

Overwrites report #4 todo list.
I'm not sure if I should start by 1. or 2. or 3.

1. ask san luciano's dataset (10 spirals with each hand of 138+150 subjects = 5760 total samples)
2. advanced transformations (cf. report #3) :
    a. dynamic time warping
    b. discrete wavelet transform
    c. power spectral density (PSD)
3. architectures of report #4 1.1 Architectures I want to implement
4. train a model on each task and merge prediction (i.e. late fusion)
5. regularization of report #4 3 Regularization & Overfitting (e.g. recurrent dropout)
6. auto encoder for report #4 4 Transfer Learning

References

Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.